Introduction to coupled atmosphere/ocean modeling and data assimilation [for NWP, Subseasonal to Seasonal Prediction, Reanalysis]

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ECCO Summer School, May 2019

Outline

- Why coupled model for NWP/Seasonal forecasts/reanalysis?
- Why coupled Data Assimilation?
- “Flavors” of Coupled Data Assimilation
- Benefits for NWP
- Critical for Sub/Seasonal Prediction
- Cautionary Tales – Strong/Weak Coupled DA and modeling
- Going Forward – Where we are as a community

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Why Coupled Models?

Benefits for NWP related to:

- **Tropical convection,**
- **Hurricanes, extra-tropical storms**
- **Coastal upwelling,**
- **Sea ice (polynyas, leads)**
- **Coupled Processes**

Beyond NWP: Extend skillful forecasts beyond two-week barrier by leveraging predictability in low frequency components (ocean, land…).

Coupled models needed to support seamless prediction, ie., single model used to span prediction timescales from weather to sub/seasonal to multiyear to decadal.

Penny et al., 2017, WMO White Paper

Why Coupled Models?

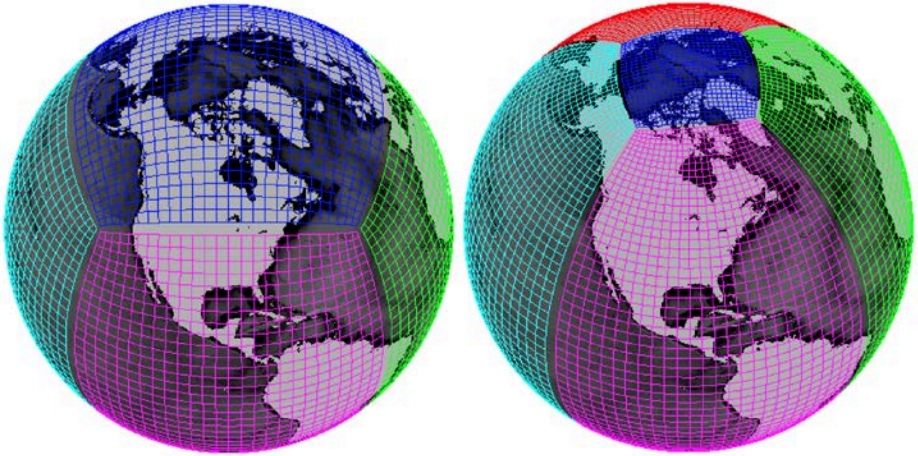
Example: Capture Air-Sea Interactions in GEOS-MITgcm coupled simulations

Atmosphere – GEOS:

- **Horizontal grid – Cubed sphere, 1/8° x 1/8°**
- **Vertical grid – hybrid sigma-pressure, 72 levels**

Ocean – MITgcm

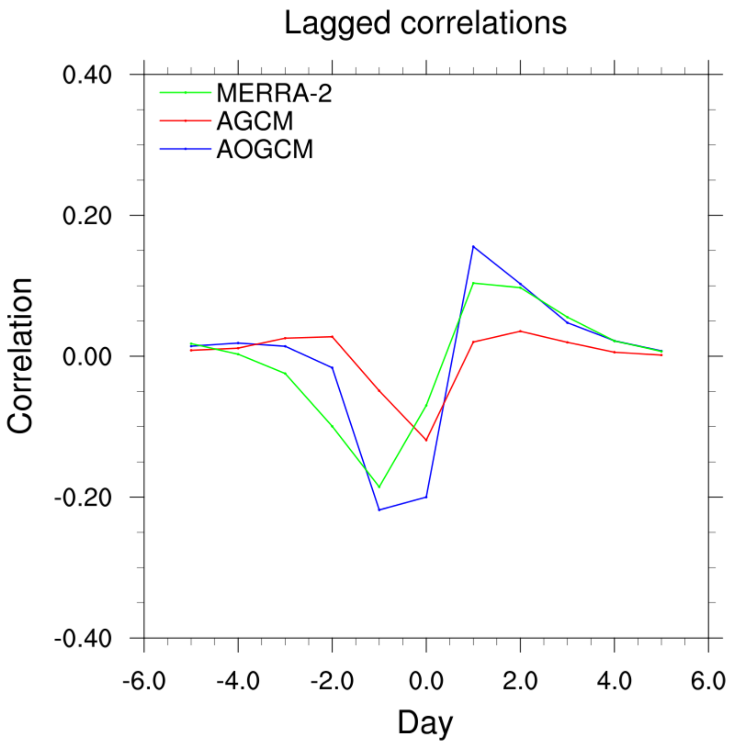
- **Horizontal grid – Lat-Lon-Cap, 1/12° x 1/12°**
- **Vertical grid – z^* rescaled height vertical coordinate, 90 levels**

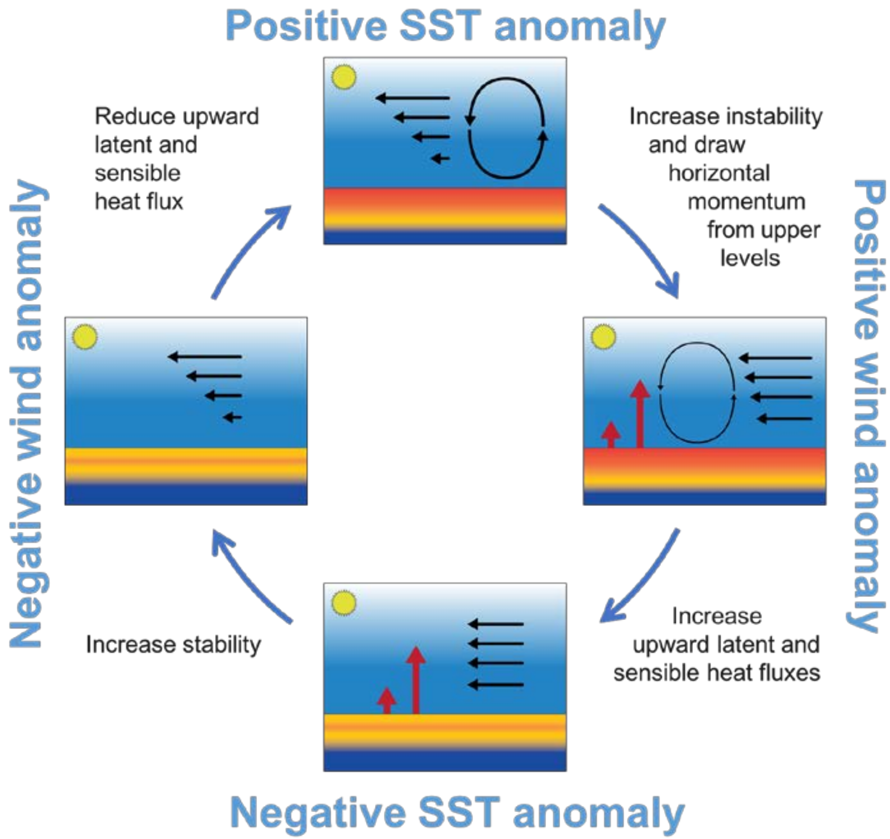


GEOS Cubed sphere grid (left) and MITgcm Lat-Lon-Cap (right)

Hourly Net heat Flux (Feb)

Why Coupled Models?

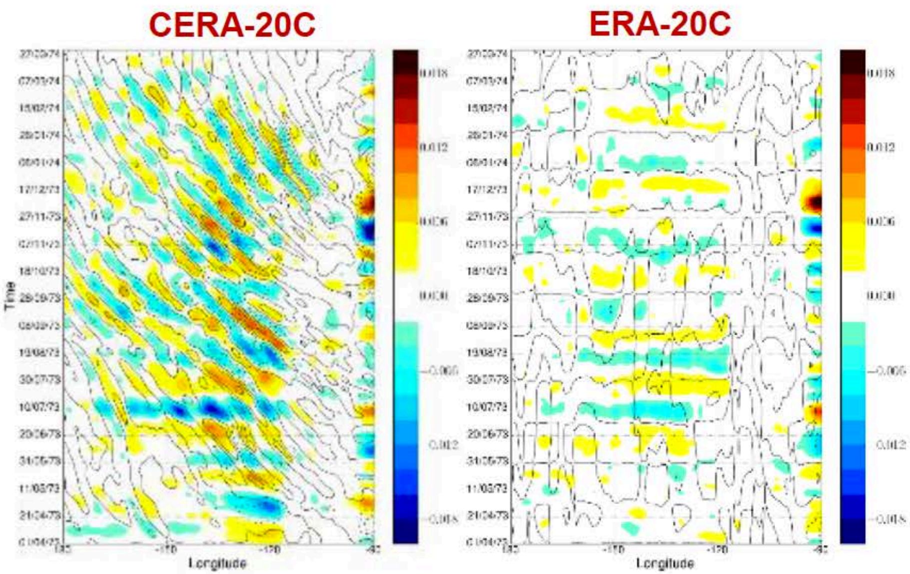




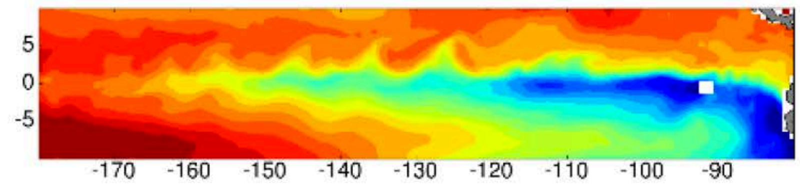
From Strobach et al., In Preparation

Why Coupled Models?

Example: Tropical instability waves (westward-propagating waves near the equator)



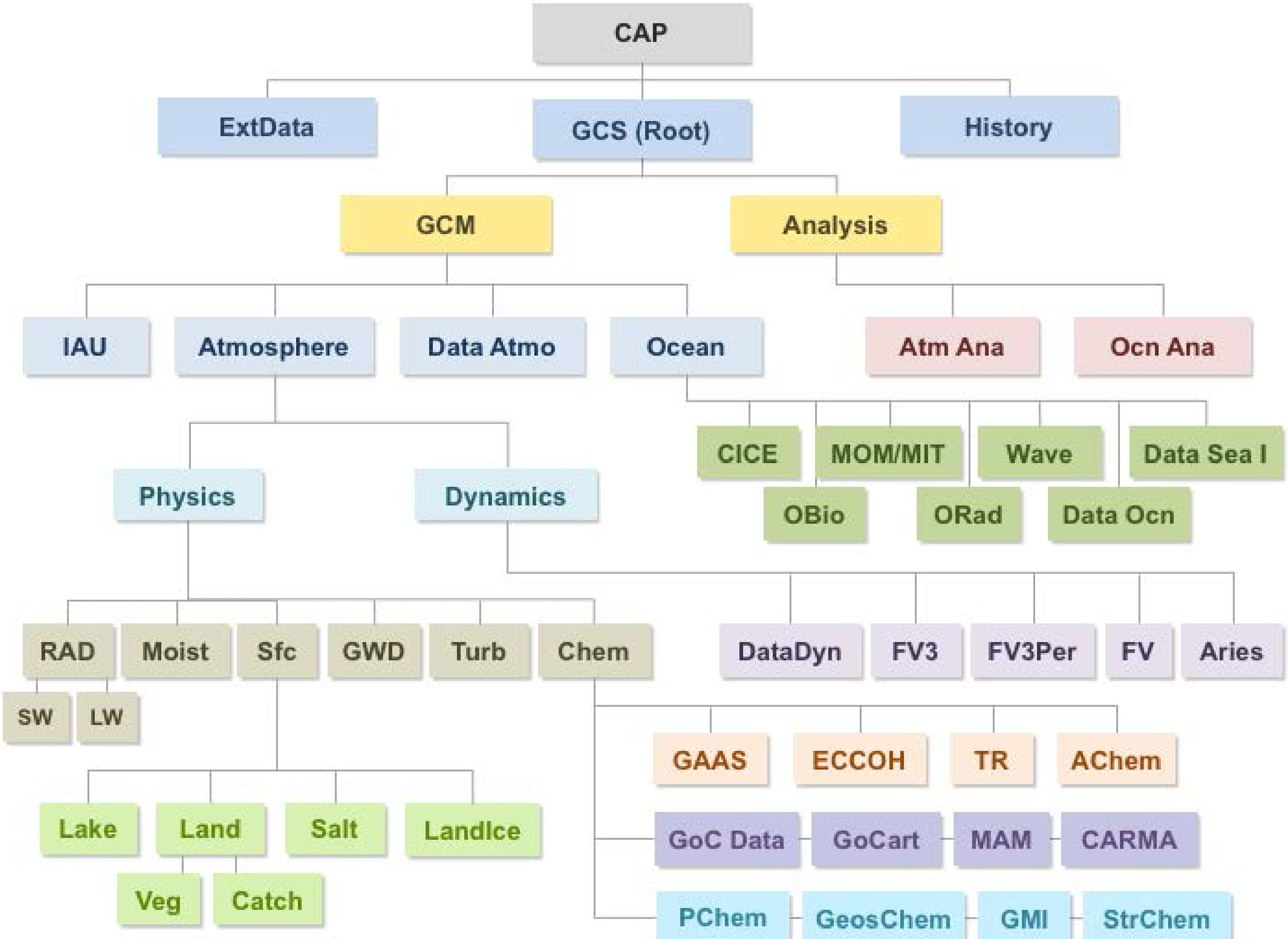
high-pass filtered SST (colour) and wind stress (contour)



Coupled Model's ocean dynamics represents TIW's, and atmosphere responds. Cannot be captured in atmosphere-only specified SSTs

Slide from: Schepers ECMWF Annual Seminar 2018

GEOS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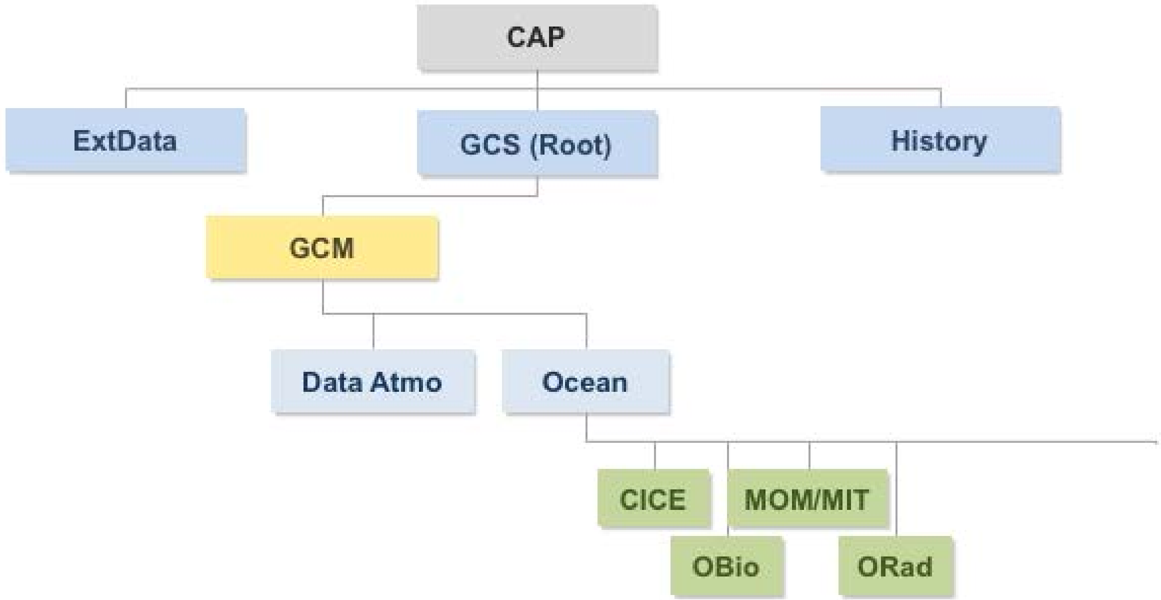
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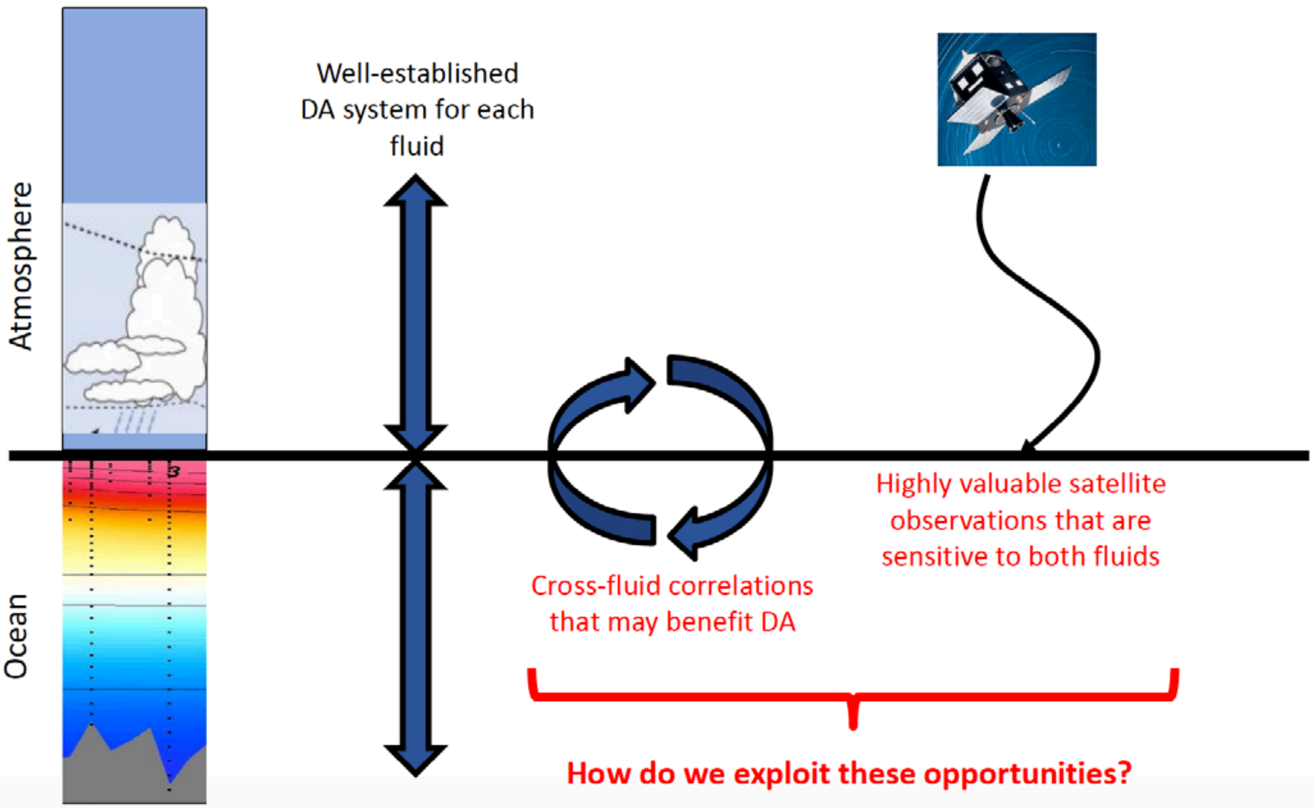
Why Coupled Data Assimilation?



Slide from: Frolov ECMWF Annual Seminar 2018

Why Coupled Data Assimilation?

Other Motivations:

- Initialization of Coupled Models
- Better treatment of physical consistency among component systems
- Errors in one system may be highly correlated with errors in others

- "The future of reanalysis lies in IESA" - Decadal Survey 2018
- "CDA provides a significant advantage over single-domain analyses and a great opportunity for improving our estimates of the Earth system state" - Penny et al. (WMP White Paper, 2017)

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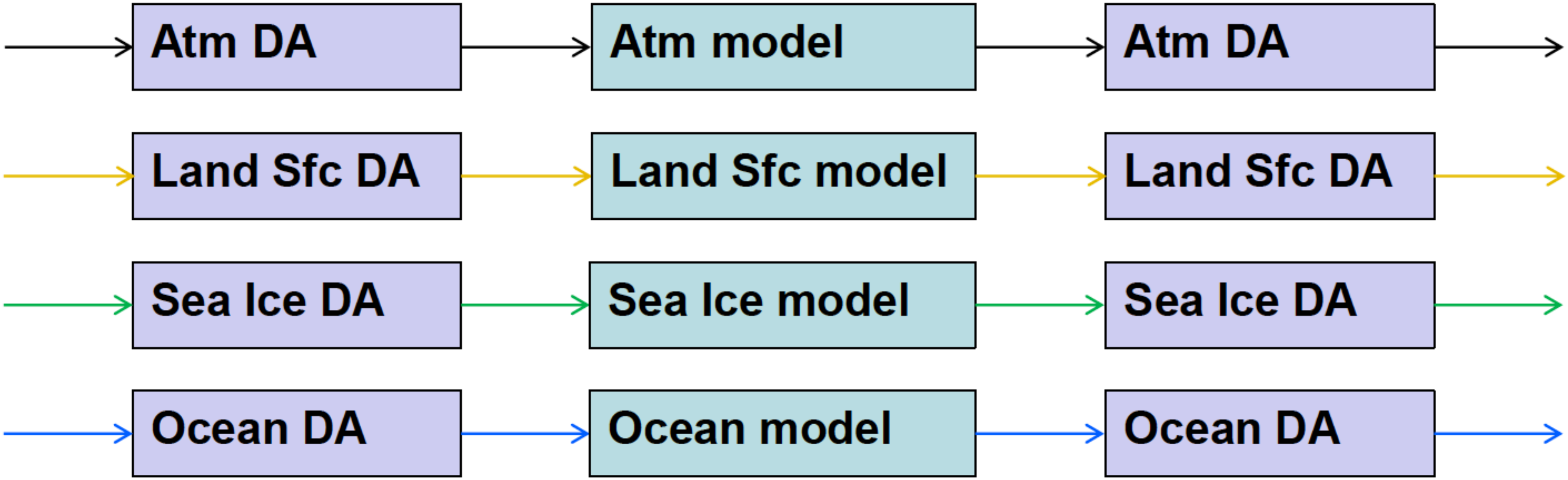
"Flavors" of Coupled Data Assimilation

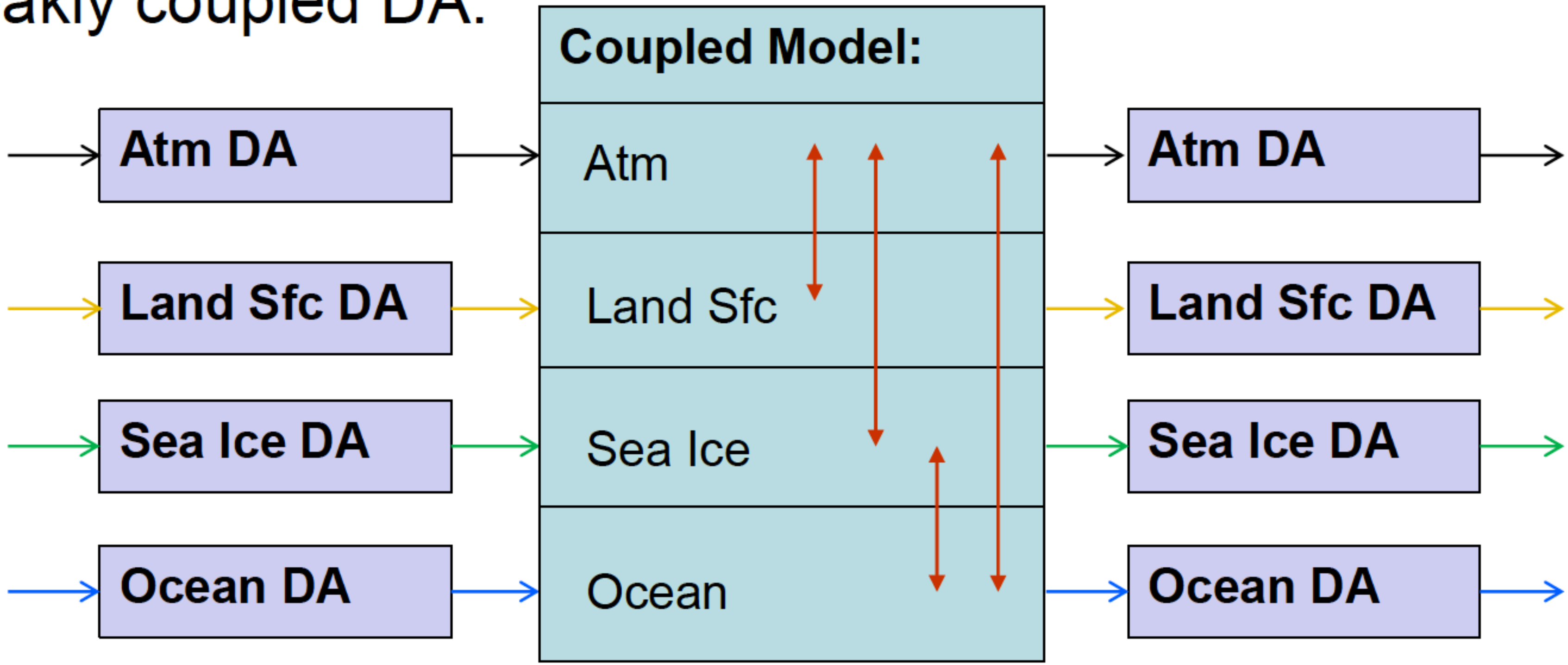
Uncoupled DA:



Concept/Slide loosely from: Mark Buehner, Environment Canada

“Flavors” of Coupled Data Assimilation

Weakly coupled DA:

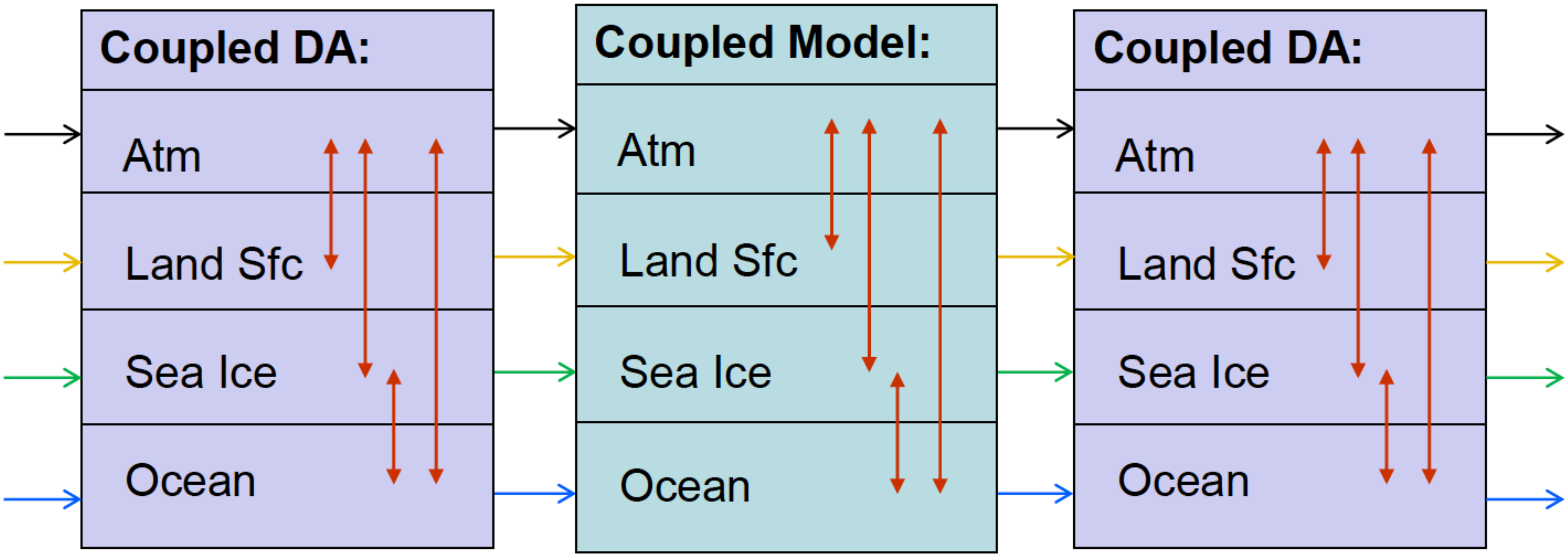


MANY!!!!! “flavors” of weakly coupled (“quasi-”) - each center has their own

Concept/Slide loosely from: Mark Buehner, Environment Canada

"Flavors" of Coupled Data Assimilation

Strongly coupled DA:



The "Gold Standard": need coupled error covariances (also: "quasi-strongly")

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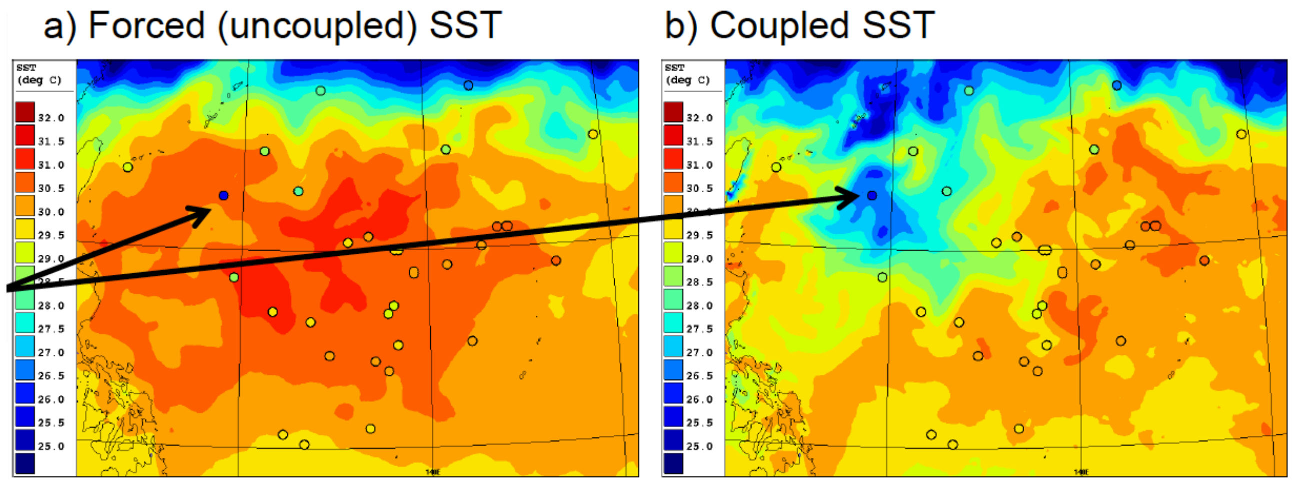
Benefits for NWP – Coupled Model

Much better agreement with drifter buoys of the SST in the cold wake behind Typhoon Neoguri

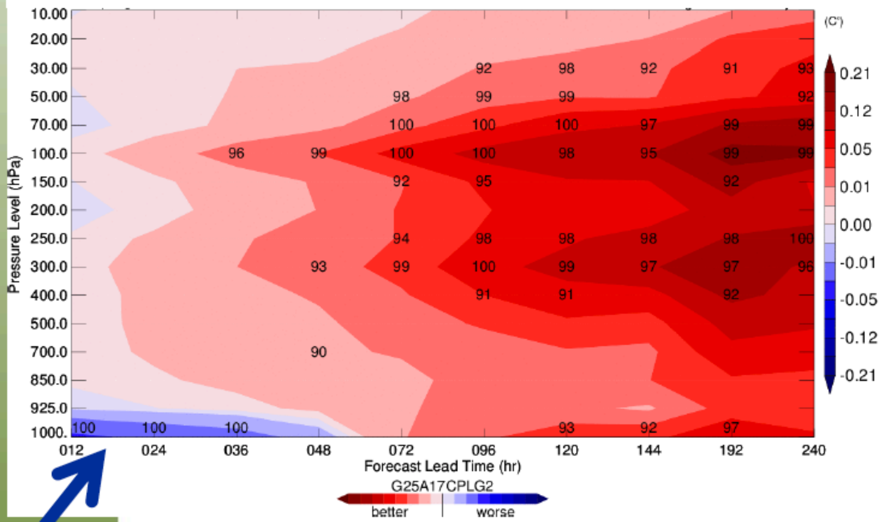


Smith et al., 2018, MWR

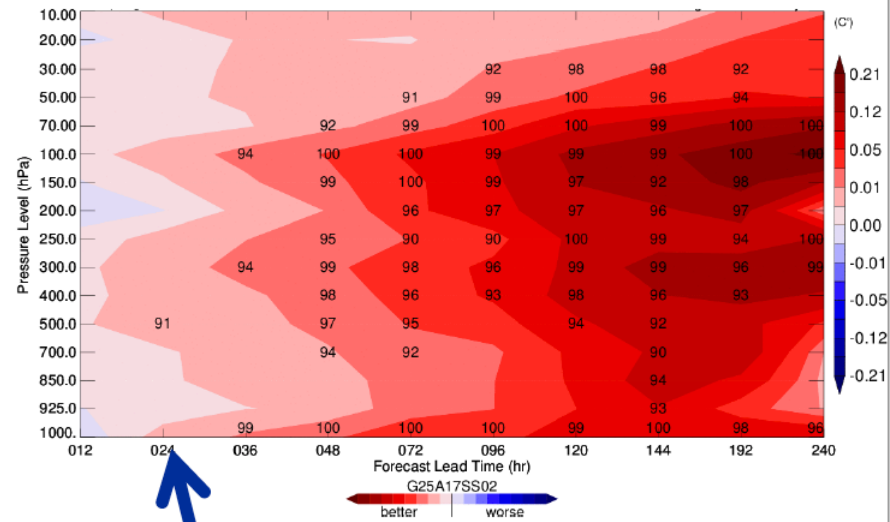
Also, from Mogensen et al (JGR 2017) – " The comparison of the upper ocean of the Haiyan and Neoguri predictions leads to the conclusion that knowledge of the vertical stratification of the ocean is crucial to being able to predict the coupled feedback and thereby predict the evolution of the tropical cyclone.

Benefits for NWP – Coupled Assimilation

Coupled forecasts from uncoupled analyses vs. uncoupled forecasts.



Coupled forecasts from weakly coupled analyses vs. uncoupled forecasts.



Coupled forecasts less consistent with own analyses for near-sfc temperature due to use of uncoupled ocean analyses

Analyses where 4D-EnVar sees the model SST are more consistent with the coupled model forecasts

Slide from: Buehner, ECMWF Annual Seminar 2018

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Scientific Basis of Seasonal Prediction

The climate system is a forced dissipative nonlinear dynamic system, and due to its chaotic nature there is a finite limit of weather predictability. Despite this….

The tropical flow patterns and rainfall, are so strongly determined by the underlying sea-surface temperature (SST) that they show little sensitivity to changes in the initial conditions of the atmosphere.

Also, the ocean (and land) evolve more slowly (the ocean takes atmospheric white noise forcing and makes it red) and so extend predictability

So - it should be possible to predict the large-scale seasonal tropical circulation and rainfall for as long as the ocean temperature can be predicted.

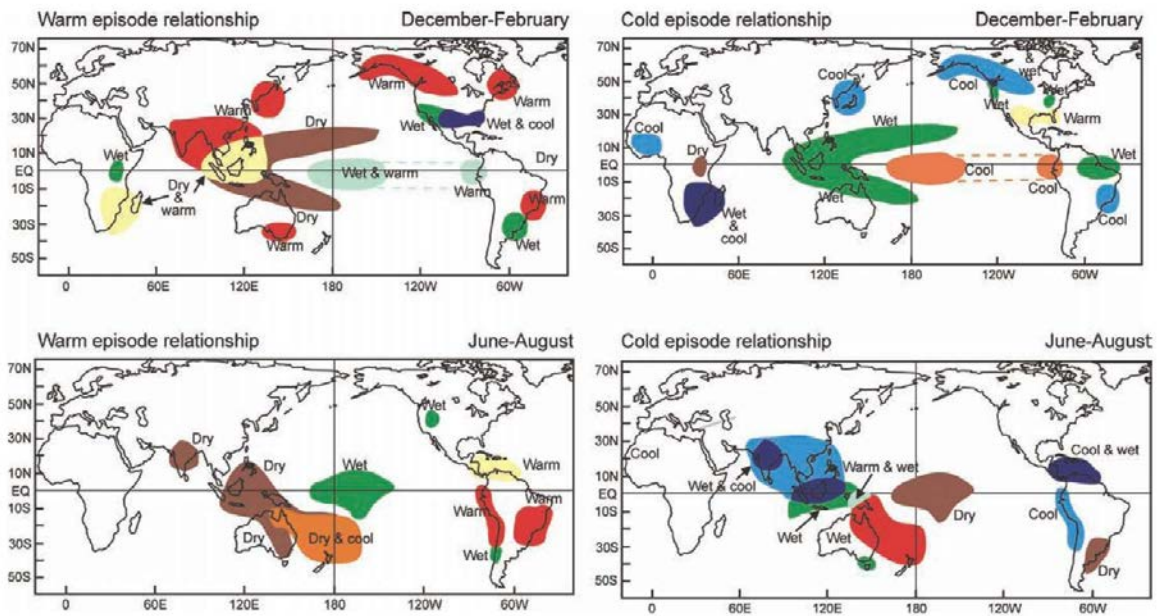
All this depends on being able to predict the tropical SST, which was shown by Seager (1989) not to depend on initial conditions but on the overlying atmosphere.

An important element is the signal-to-noise (S/N) ratio, which represents the relative proportion of the climate variability that is potentially predictable. The predictable portion (the signal) depends on SST or other boundary conditions. The remainder of the climate variability is related to fluctuations internal to the atmosphere (the noise), which is generally unpredictable

Scientific Basis of Seasonal Prediction (cont’d)

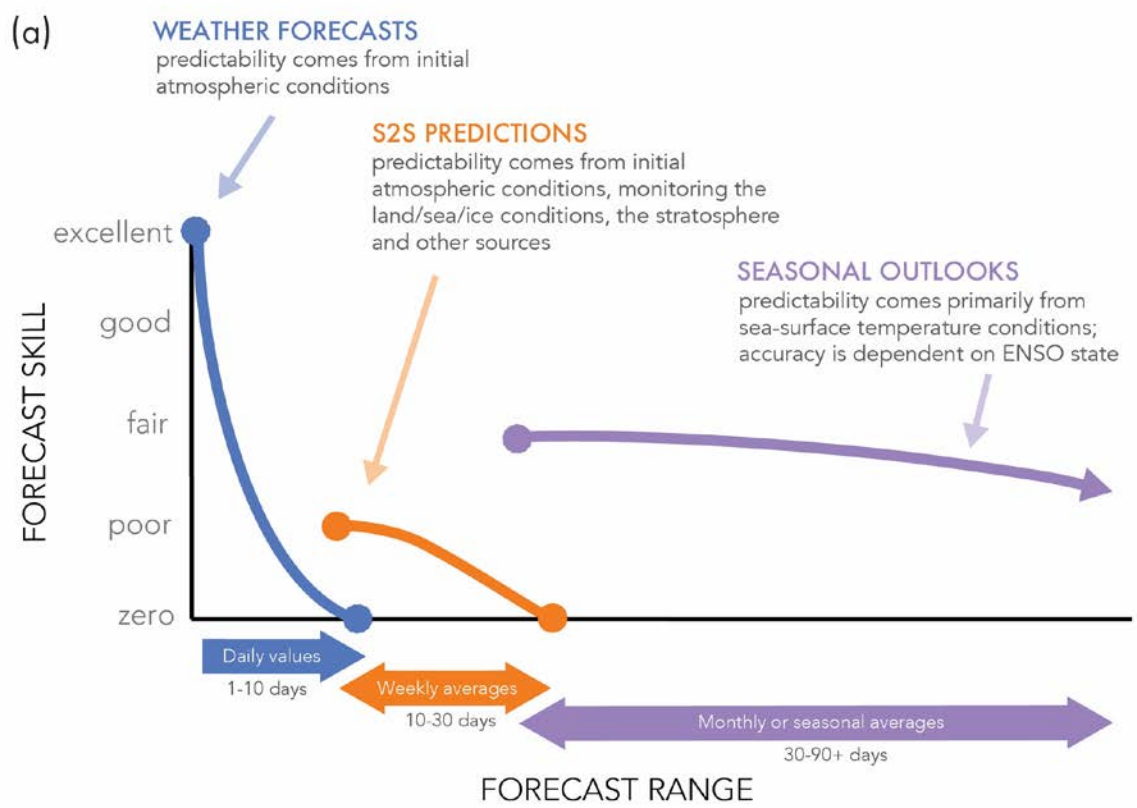
ENSO is the biggest driver of seasonal prediction and predictability, but other modes of variability contribute as well, ie., NAO, PNA, IOD.

Atlantic SST is important too, gradients of SST (Atlantic dipole) can impact the location of the Atlantic ITCZ. The Atlantic Meridional Mode is also a strong mode of variability there.



Extratropical predictability is mostly based on ENSO (and other mode) teleconnection patterns

Scientific Basis of Seasonal Prediction (cont’d)



https://www.weadapt.org

History of Seasonal Prediction

1877: Indian drought and famine (tied to the 1876-8 El Niño) prompted the Indian meteorological department to start forecasting monsoon rainfall based on Himalayan snowfall in previous winter.

1923,24: Walker detected large scale patterns, called them the Southern, North Pacific, and North Atlantic Oscillations. He developed a linear regression model for prediction of precipitation based on these patterns

1930s: In wake of Dust Bowl, funding of research by Rossby and Namias working on long range wave propagation

IGY (1957,58): Observations revealed that a major die off of seabirds off Peru and the appearance of tropical fish off California were for the first time connected to a much larger climate phenomenon.

In 1970's the relationship between SO and El Niño was identified, and saw teleconnections between tropical SST anomalies and remote areas.

The 1972-73 El Niño had global economic implications, and prediction took on new significance. Ten years later, the biggest El Niño of the century at that time (1982-83) peaked before the scientific community agreed it was happening.

History of Seasonal Prediction (cont'd)

The Zebiak and Cane (1987) model was the first to describe self-sustained, continuously coupled oscillations arguably like the real ENSO. They also produced the first successful prediction of El Niño by forecasting the 1986–1987 event 12 months in advance (Cane et al., 1986).

An important focus of research in the 1990's was the tropical Pacific sea surface temperatures as an important parameter for seasonal prediction.

Dynamical seasonal prediction systems have been operational since ~2000. There are 10 major Global Producing Centres (GPCs) of Long Range Forecasts as identified by the World Meteorological Organization (WMO) (http://www.wmo.int/pages/prog/wcp/wcasp/clips/producers_forecasts.html).

Multi-model ensembles are assembled by, eg., NMME, EuroSIP, APCC (Korea)

Most recently: Multi-model seasonal sea ice prediction, aerosol prediction

Practicalities of Seasonal Prediction

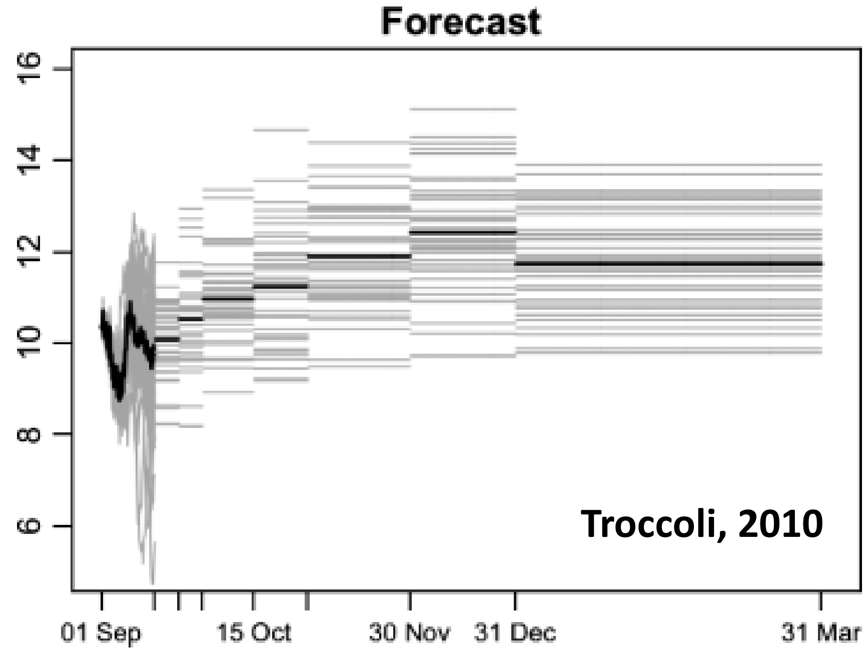
What is predictable at Seasonal Lead Times?

- **Time averages**
- **Spatial averages**
- **Probabilistic Measures (PDFs)**

Ensemble forecasts needed to predict PDFs, must assess reliability

Forecasts require calibration, or removal of mean bias or of mean bias and variance (standardization). For this we need reforecasts. Calibrated forecasts are more reliable.

Multi model ensembles help (Krishnamurti et al., 1999; Palmer et al., 2004) skill, but not clear why. It does reduce overconfidence.

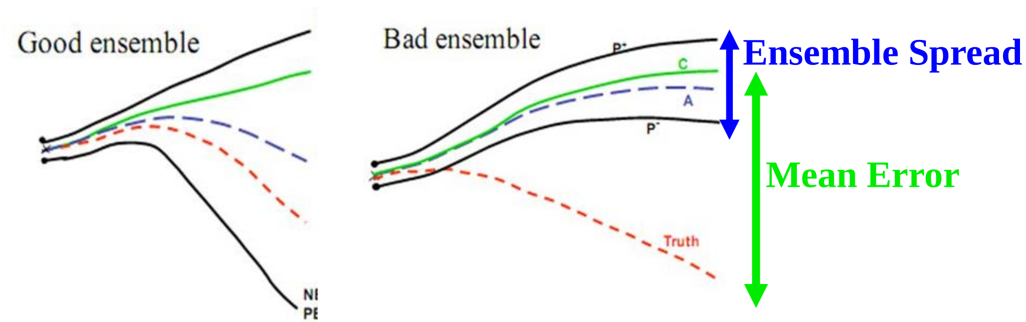


The longer the lead time, the longer the period of time average needed. This increases the signal to noise ratio enough to obtain reliable forecasts.

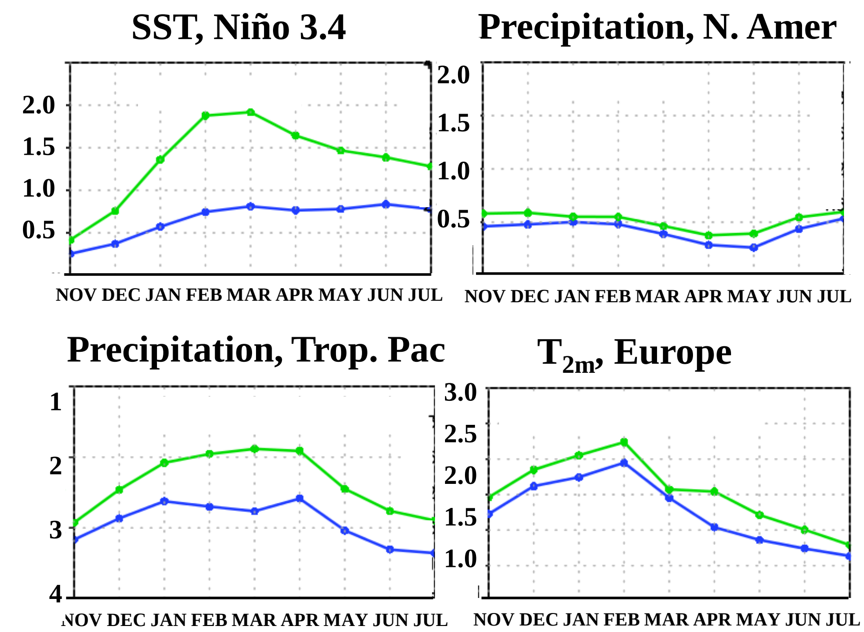
Probabilistic Evaluation: Forecast "Confidence"

Evaluate "confidence" by comparing:

- Ensemble spread (distance among members)
- Mean Error (mean of error of individual ensemble members)



Kalnay, 2003



Spread too low over the ocean "overconfident"

Spread is good over land, confidence matches skill

Images from: Zhao Li

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Cautionary Tales – Strongly Coupled DA

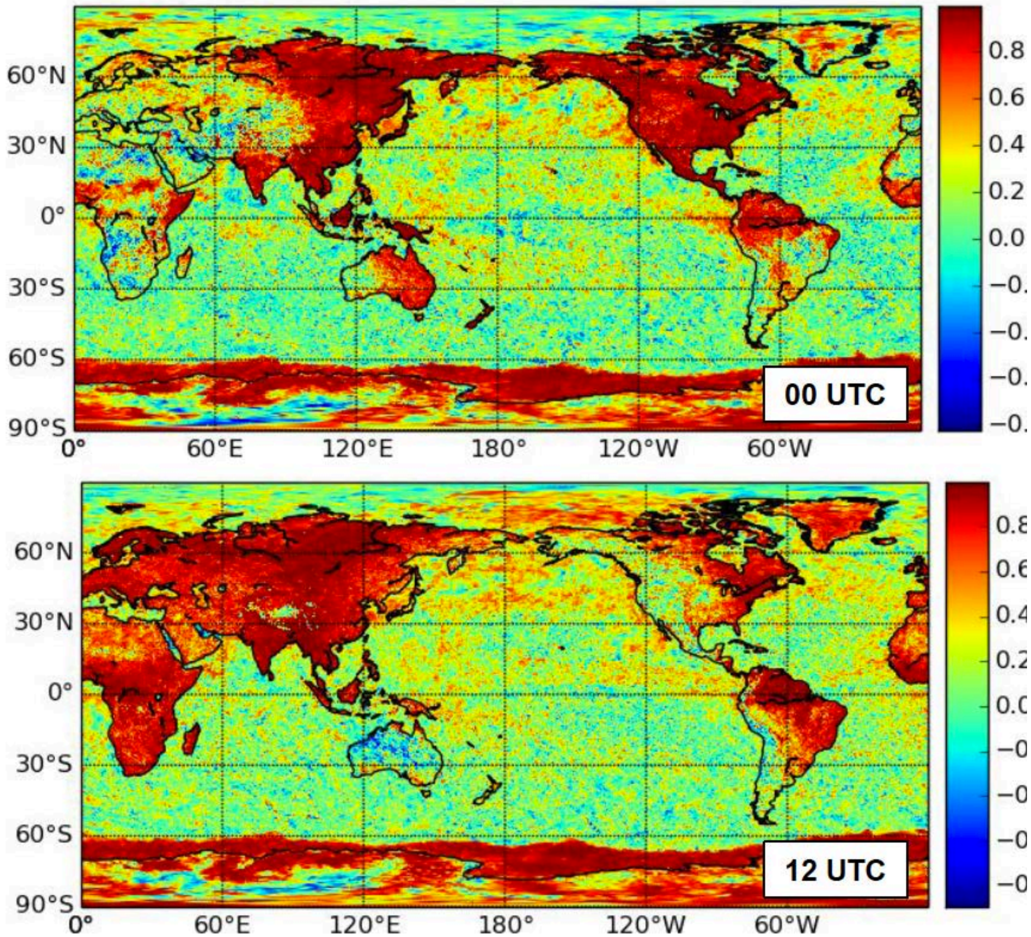
Strongly Coupled Data Assimilation requires accurate representation of coupled error covariances – they are difficult to estimate:

Frolov et al (MWR 2016) – ".. in the presence of poorly known error covariances, the interface solver [weakly coupled] can be configured to produce a more accurate solution than an exhaustive solver [strongly coupled]."

Lu et al (MWR 2015) – …in a perfect model framework, "SCDA system could significantly reduce the RMSE of monthly SST analysis over most regions compared to the WCDA…. With a realistic model bias there may be a need for a longer data window and a better set of cross-covariances

Smith et al (MWR 2017) – "… for strongly [coupled DA] the cross-covariances are critical… strongest error cross correlations are seen in the near-surface atmosphere–ocean boundary layer, but beyond this the atmosphere and ocean errors appear to be mostly uncorrelated. Within the boundary region there is notable variation in the strength and structure of the error cross correlations between summer and winter, and also between day and night.

Cautionary Tales – Strongly Coupled DA



Background error correlation of near surface air temperature and skin temperature

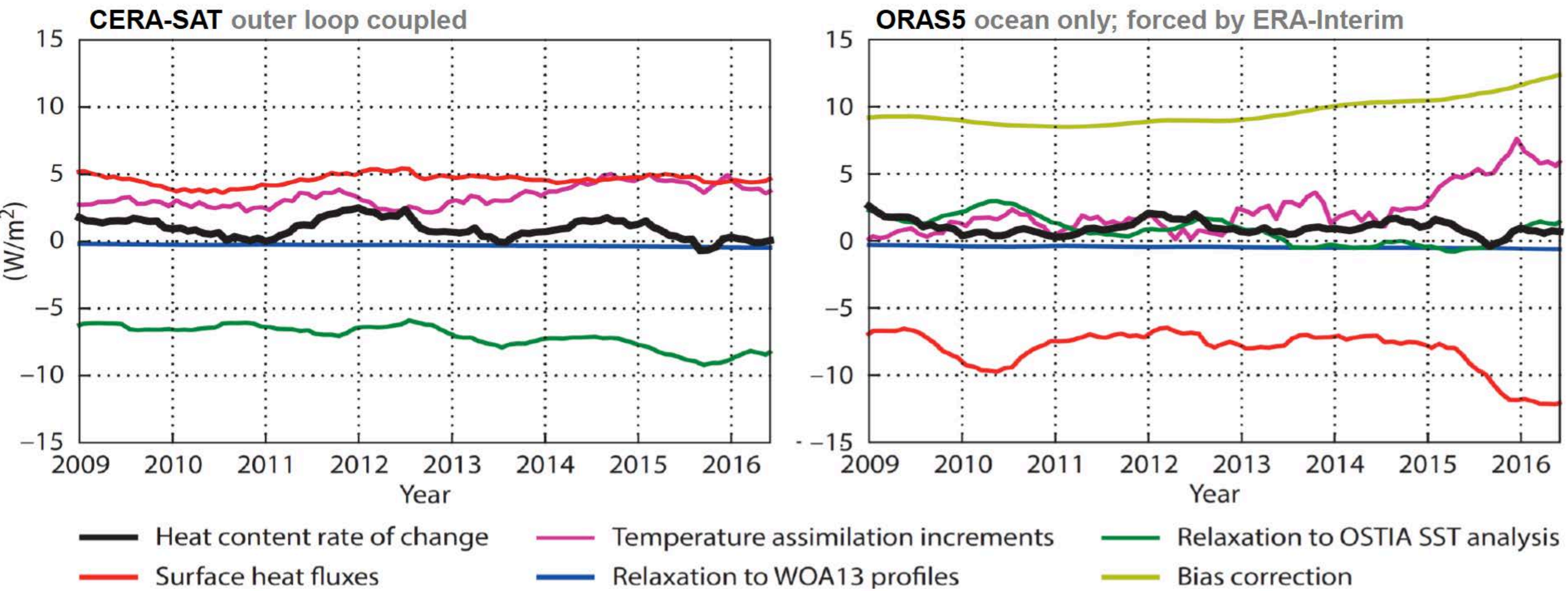
See relatively coherent and steady structure over land, over ocean more "spotty" and variable

from: Frolow et al, (MWR, 2016)

Cautionary Tales – Strongly Coupled DA

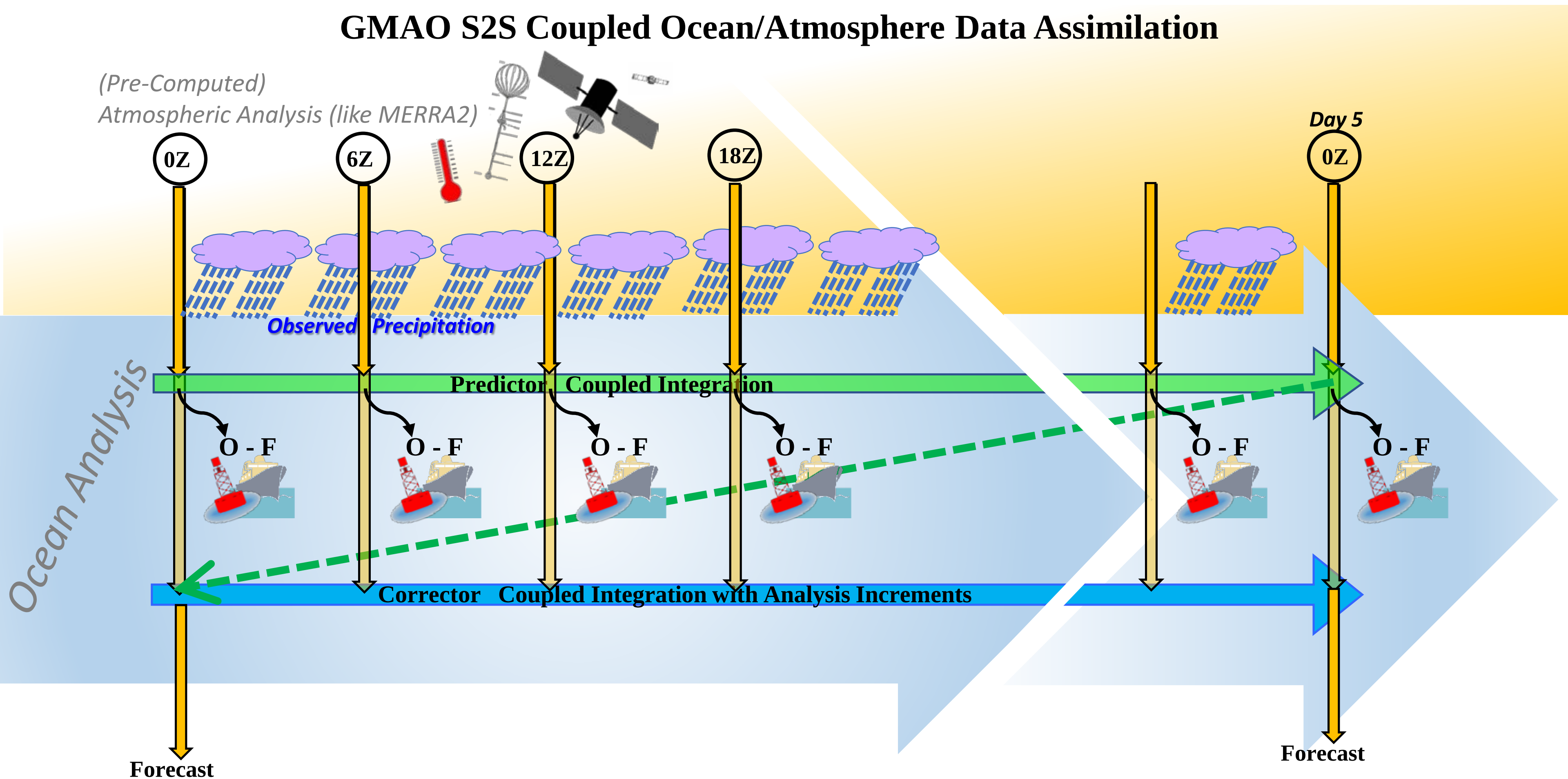
Global ocean heat budget decomposition - Comparing CERA-SAT and ORAS5

- Total global heat content rate of change (**Black**) very similar
- Although contributions from individual sources differ significantly



Slide from: Rosnay, ECMWF Annual Seminar 2018

Cautionary Tales – Weakly Coupled DA



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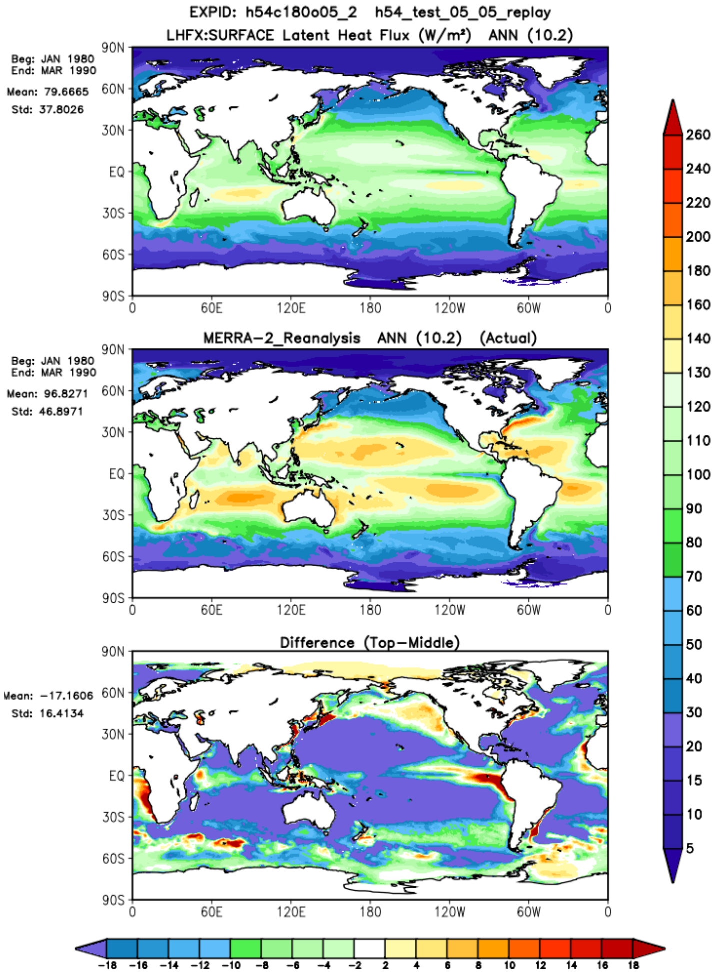
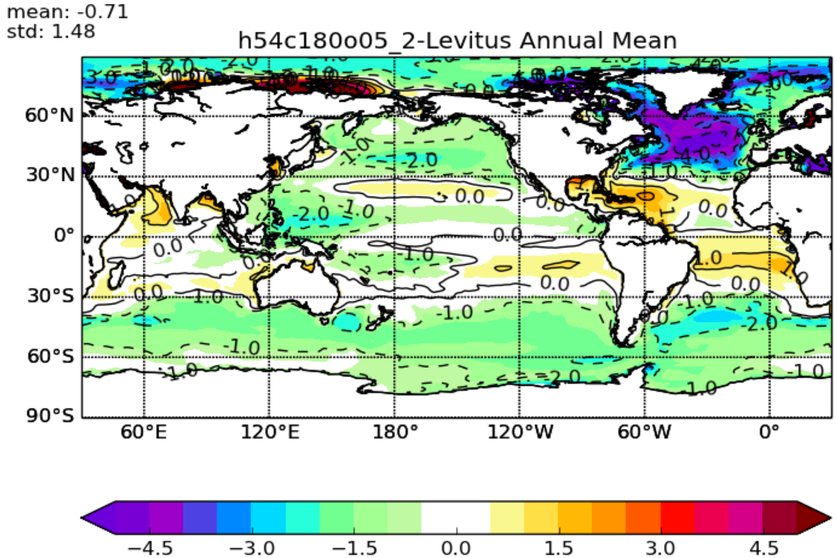
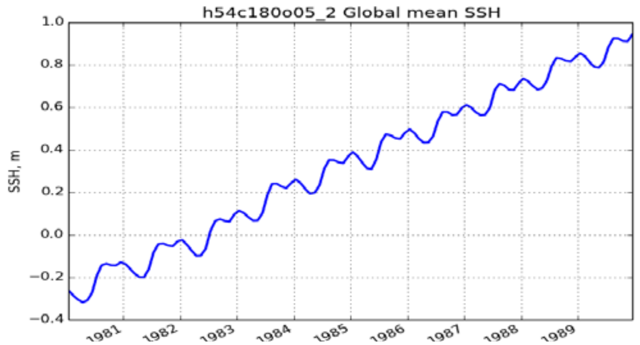
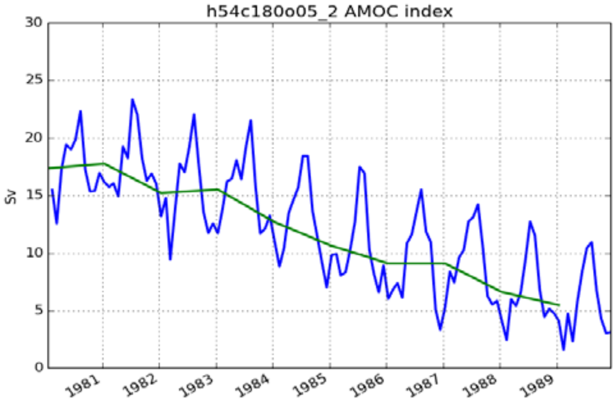


- **During Atmospheric DA the lower atmosphere "saw" a different SST than is predicted in coupled model**
- **Near surface instability decreased**
- **Latent heat flux was reduced to values that are 30% lower than the latent heat produced by the Atmospheric Data Assimilation (MERRA-2)**

Cautionary Tales – Weakly Coupled DA







Reduced Latent Heat Resulted In:

- **Freshened Ocean**
- **Sea Level Rise**
- **Weakened AMOC**

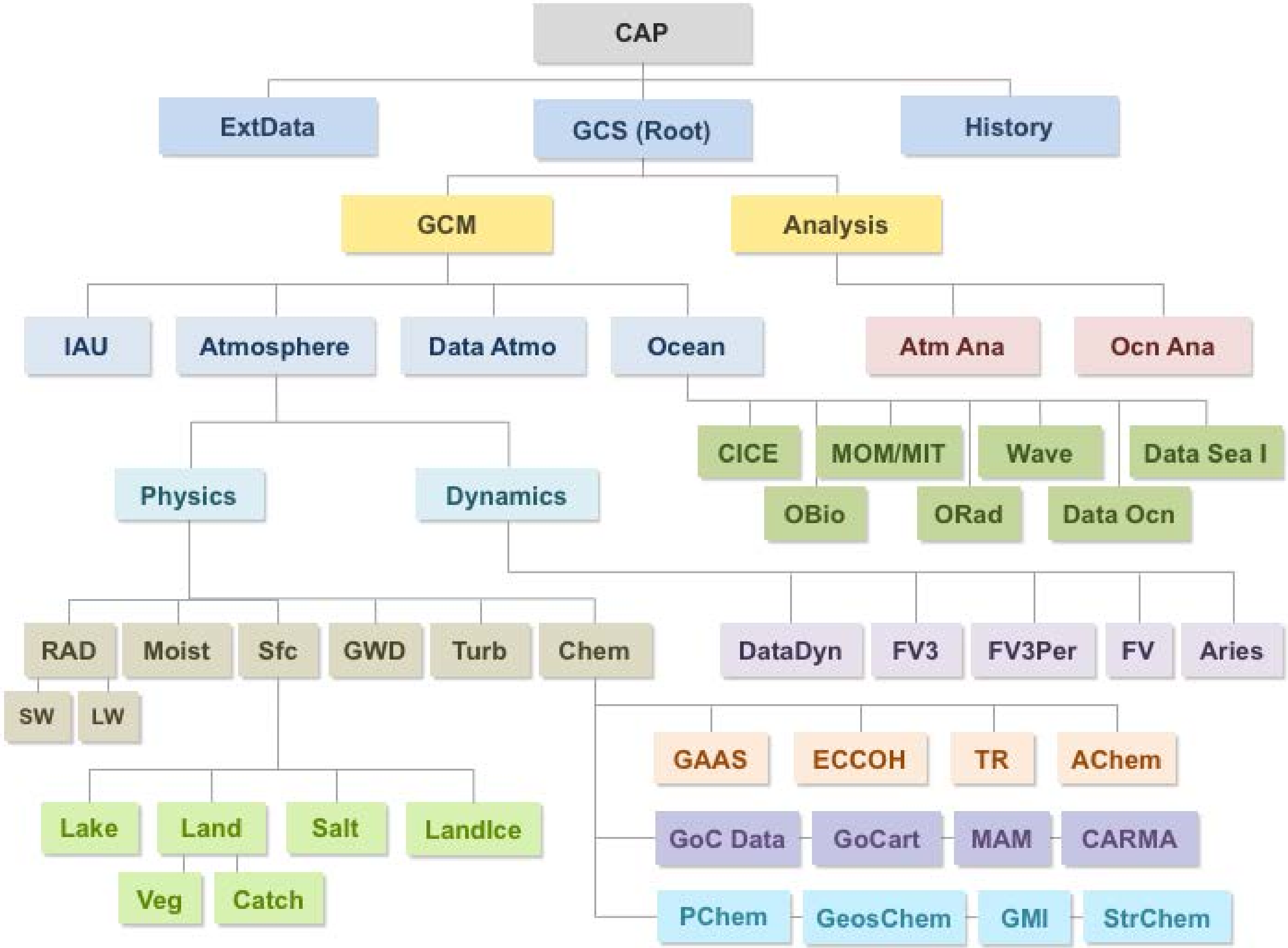
Cautionary Tales – Weakly Coupled DA

NASA/GMAO Solution: "Dual Ocean"

Basic idea: Compute near surface stability and latent heat flux (bulk formulae) using the SST that the data assimilation (MERRA-2) "saw"

Note: This reduces the level of weak coupling, is analogous to strong relaxation of SST as is done in other weakly coupled systems (NCEP)

GEOS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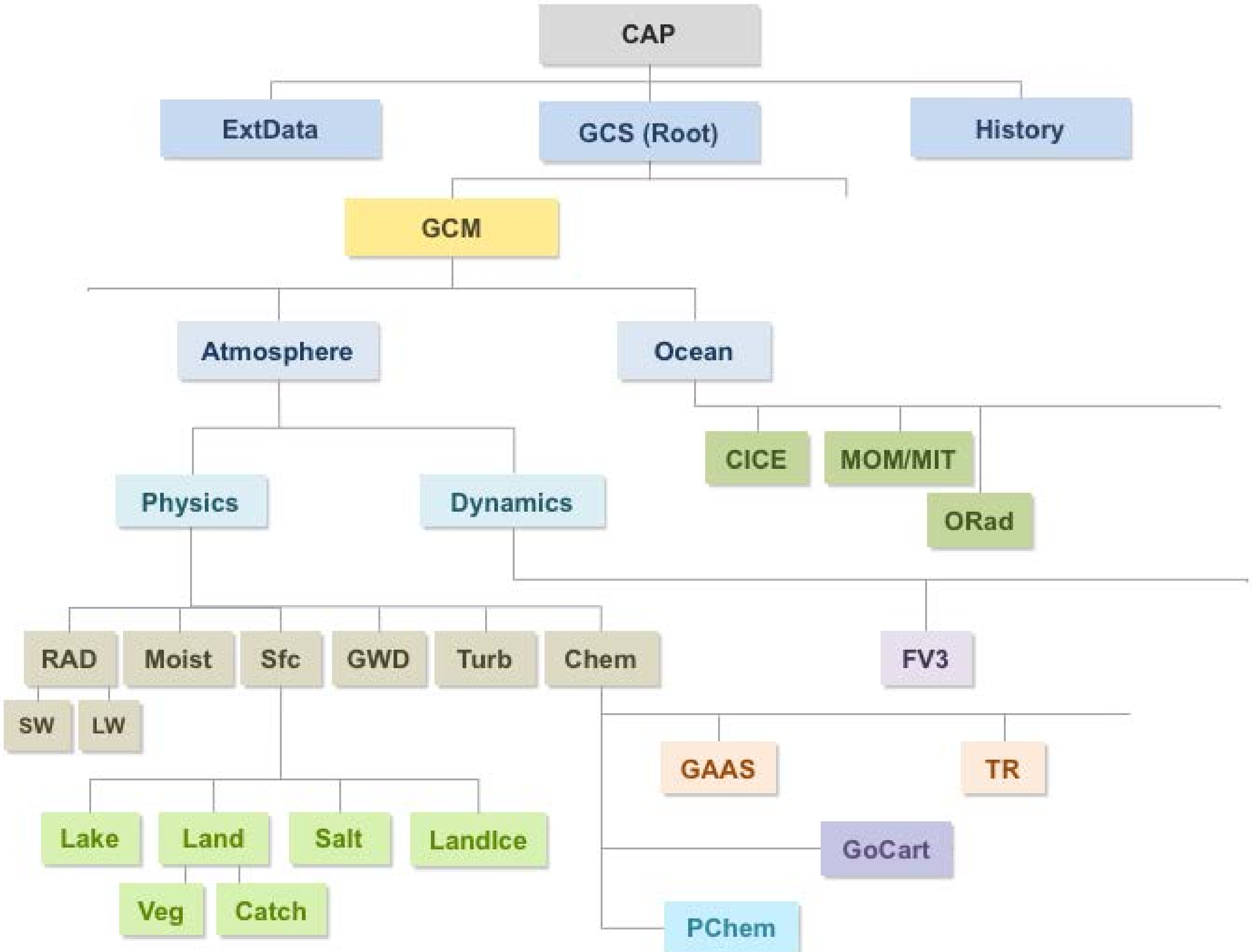
StrChem

GEOS AOGCM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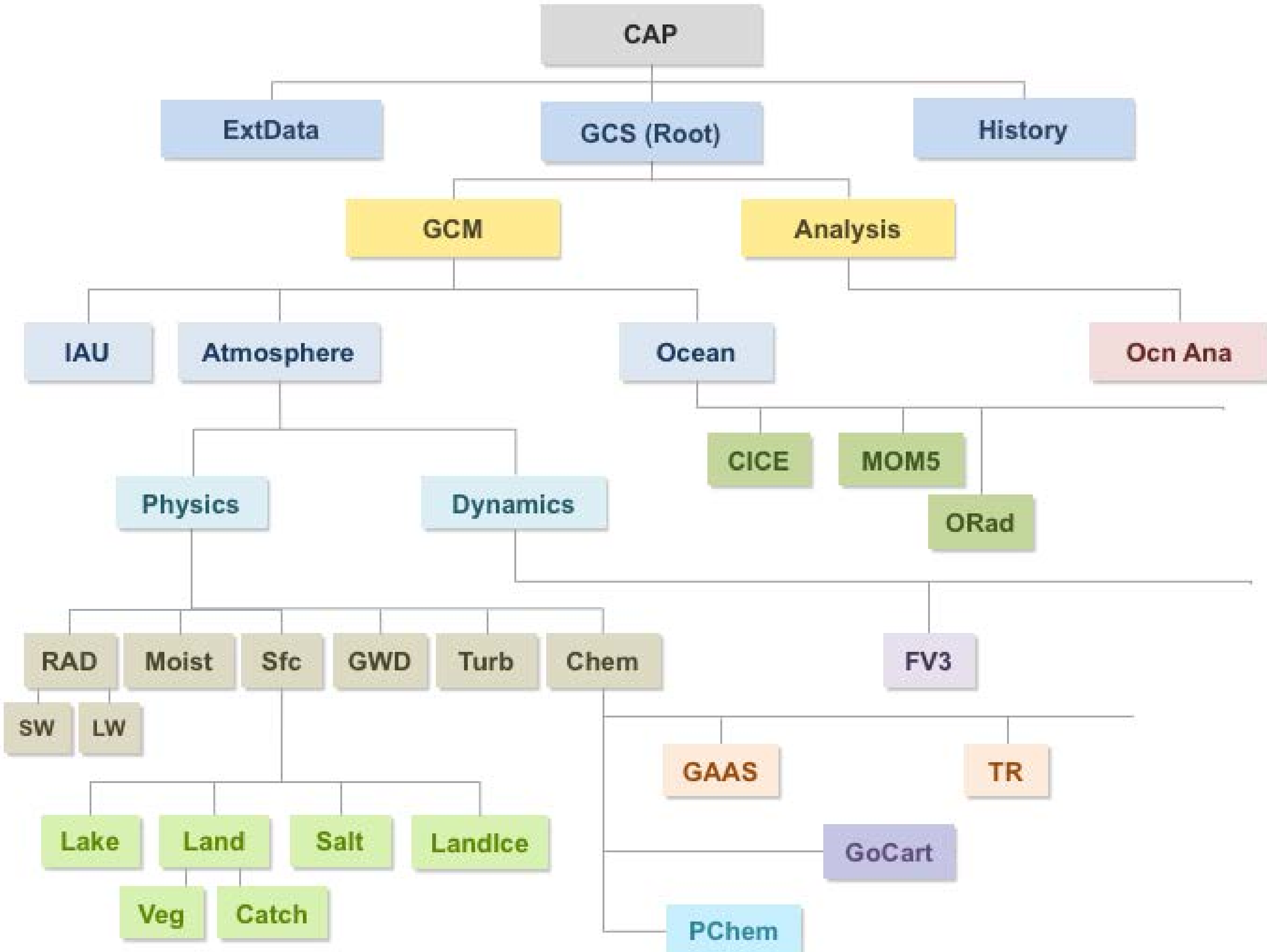
GEOS AODAS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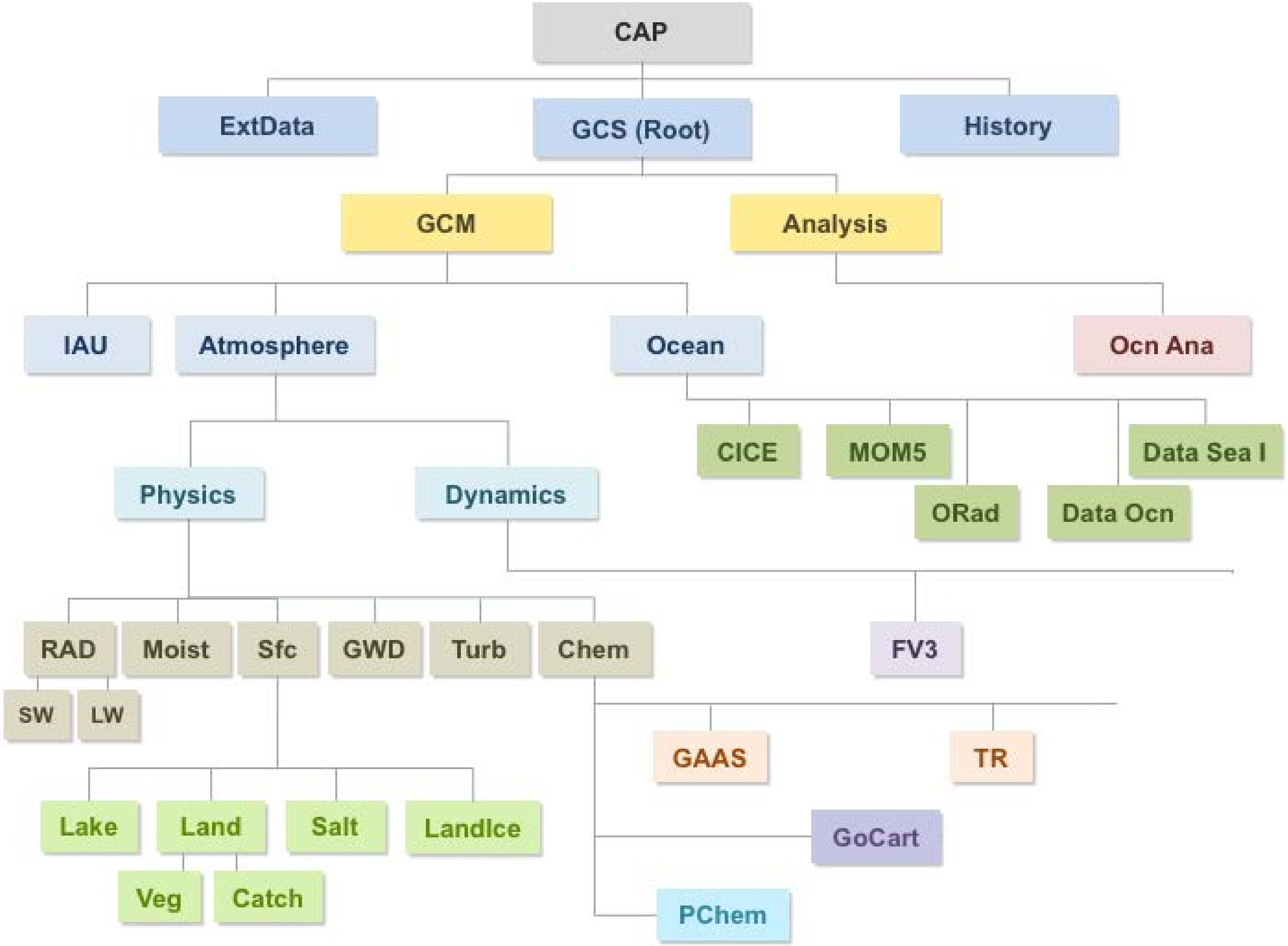
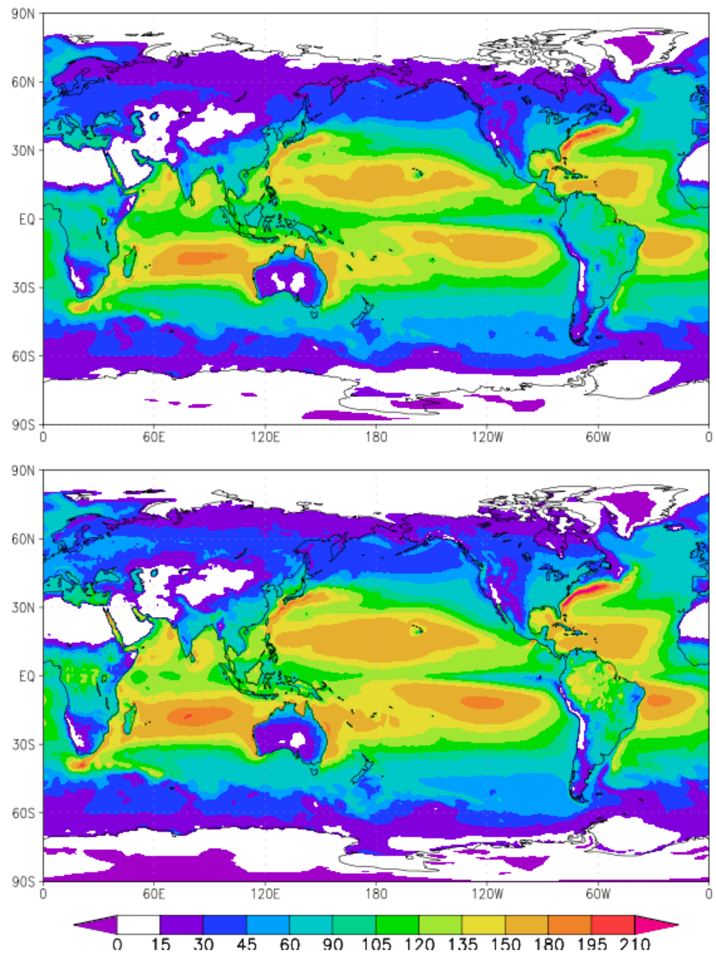
GEOS AODAS + Dual Ocean



Cautionary Tales – Weakly Coupled DA

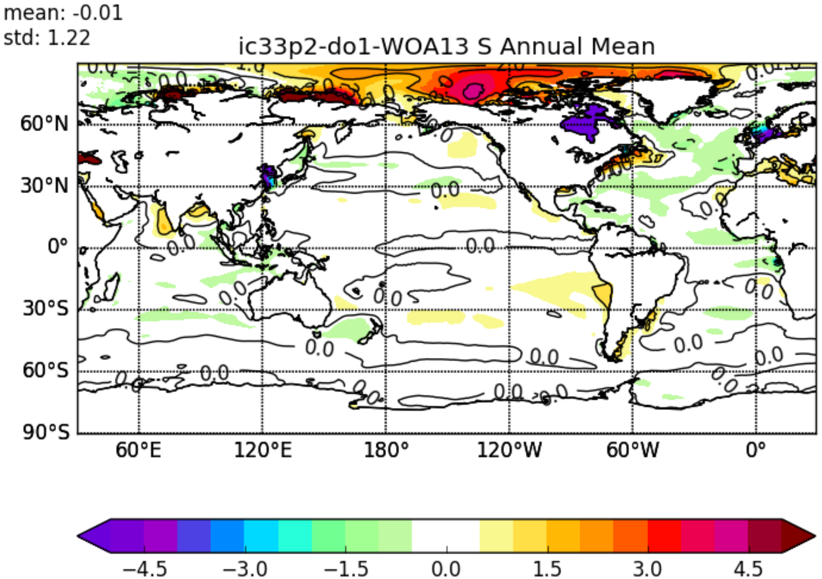
“Dual Ocean” Latent Flux

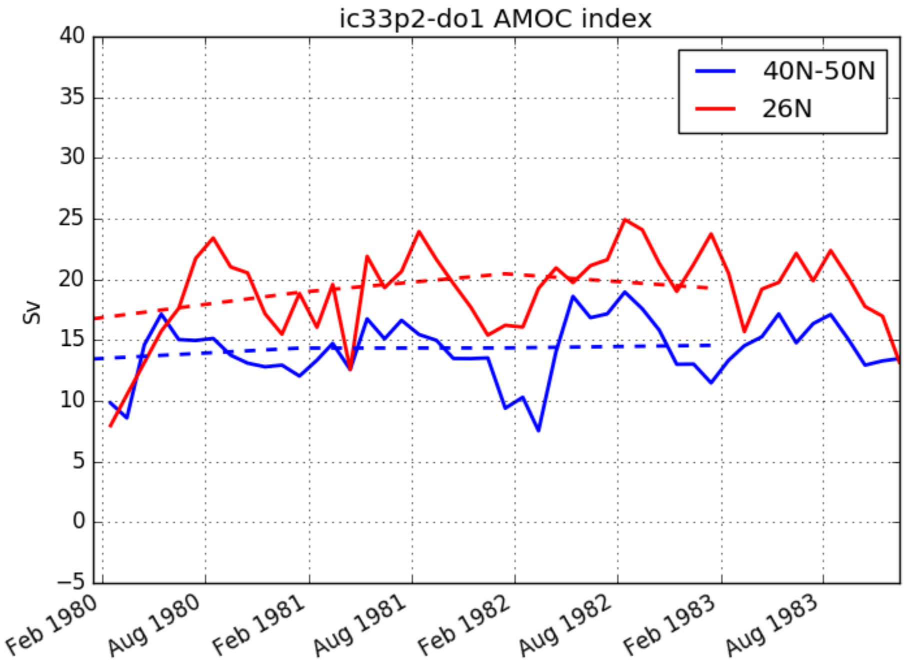
MERRA-2 Latent Flux



Using weakly coupled assimilation with “dual ocean”, latent heat flux was increased to within 5% of MERRA-2

Cautionary Tales – Weakly Coupled DA



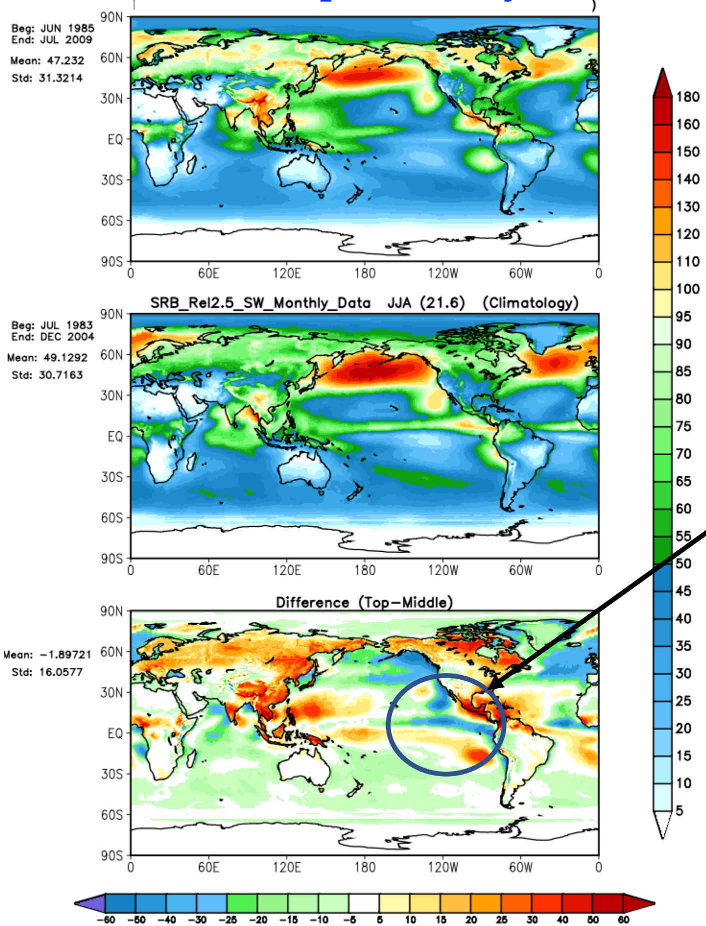


“Dual Ocean” Resulted In:

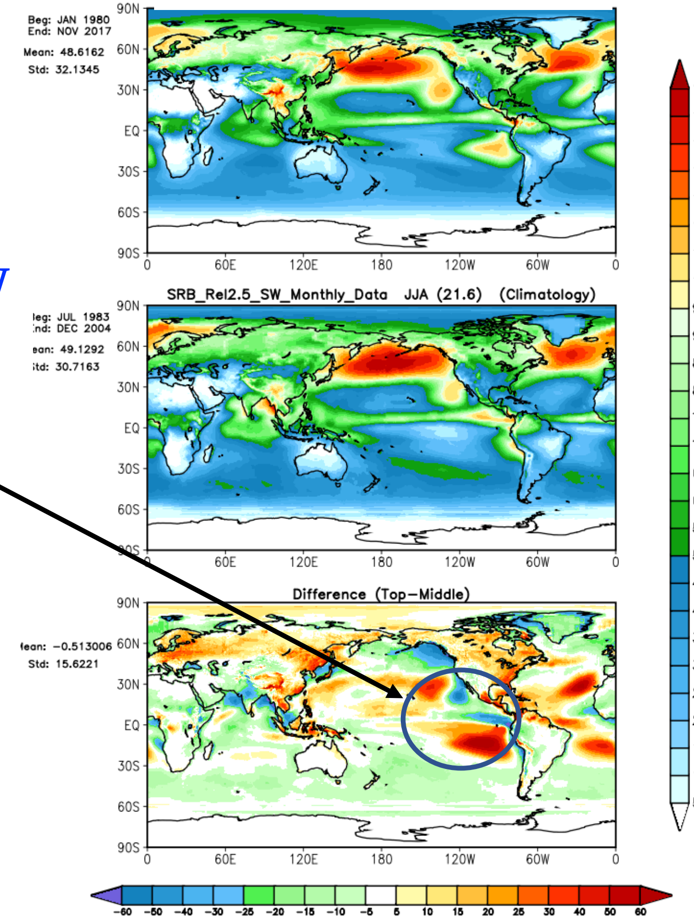
- **Improved surface salinity**
- **Steady AMOC**

Cautionary Tales – Coupled Modeling

Atmosphere Only



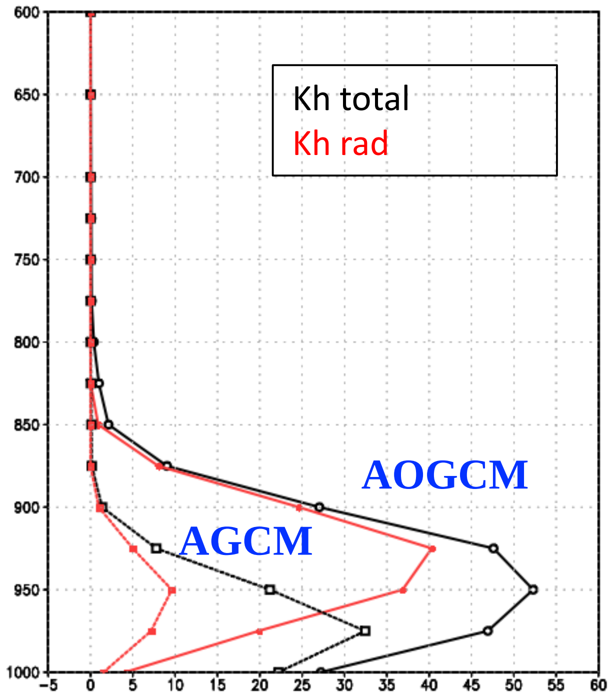
Coupled



Surface SW Cloud Effect

Cautionary Tales – Coupled Modeling

Profiles in Circled Region



Eddy Diffusivity (kg m s^-2)

Cloud Effect too large

Cold Ocean

Increased Turbulent Mixing/Surface evap reaches cloud height

Colder Atmosphere/ Higher RH/Increase Cloud Effect

MUST not set this off – bias on warm side (less cloud) better

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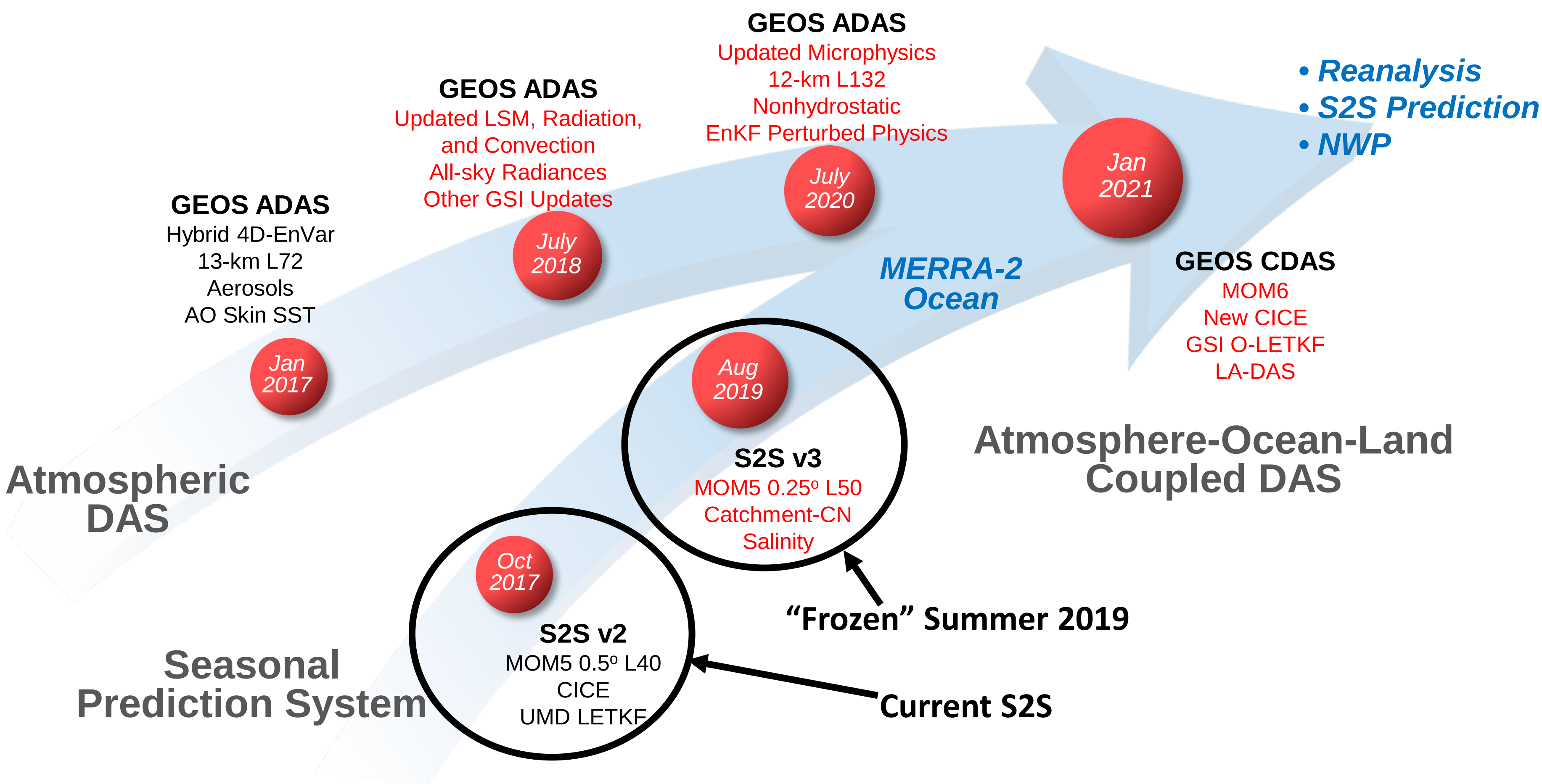
- Critical for Sub/Seasonal Prediction
- Cautionary Tales – Strong/Weak Coupled DA and modeling
- **Going Forward – Where we are as a community**

GMAO coupled data assimilation development



Status of Coupled data assimilation development/plans

Center	WCDA	Comments/WCDA	SCDA	Comments/SCDA
ECMWF			✓	"Quasi-strongly" – Coupled model in outer loop
NOAA	✓	Plan to do all prediction with coupled		
JMA	✓	Transition from quasi-weakly to weakly		
JAMSTEC	✓	Exploring	✓	Experimental system exists
BoM	✓	Used for seasonal-multi-year prediction	✓	Exploring – assimilate ocean observations and pre-computed atmosphere assimilation
Met Office	✓	Operational use		
NASA	✓	Near-real time for sub/seasonal	✓	Exploring
NRL	✓	Planning	✓	Exploring – will use coupled ensembles to compute background error – separate analysis
NCAR	✓	In use	✓	Intend to explore
ECCC	✓	Under development	✓	
GFDL	✓	In use	✓	Developing "Ensemble CDA"